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Data for: Testing the race model in a difficult redundant signals task

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Abstract

In the redundant signals task, participants respond, in the same way, to stimuli of several sources, which are presented either alone or in combination (redundant signals). The responses to the redundant signals are typically much faster than to the single signals. Several models explain this effect, including race and coactivation models of information processing. Race models assume separate channels for the two components of a redundant signal, with the response time determined by the faster of the two channels. Because the slower processing times in one channel are cancelled out by faster processing in the other channel, responses to redundant signals are, on average, faster than to single signals. In contrast, coactivation models relate the redundancy gain to some kind of integrated processing of the redundant information. The two models can be distinguished using the race model inequality (Miller, 1982, *Cognitive Psychology*, 14, 247–279) on the response time distribution functions. Miller's prediction was derived for experiments with 100% accuracy, and despite corrections for guesses and omitted responses, it is limited to easy tasks with negligible error rates. In this article we generalize Miller's inequality to non-trivial experimental tasks in which systematically incorrect responses may occur. The method is illustrated using data from a difficult discrimination task with choice responses.

R code

Data

Excel files with the following variables

- stimA: 0 for catch trial, a for weak auditory stimulus, A for strong stimulus

- stimV: 0 for catch trial, v for weak visual stimulus, V for strong stimulus
- tau: SOA in milliseconds (> 0: V before A, < 0: A before V)
- resp: response of the participant (1 = “weak”, 2 = “strong”)
- RT: response time in milliseconds
- ACC: Accuracy
- ITI: foreperiod in milliseconds
- Block: experimental block
- estim_SOA: ignore
- deltaA: distance from “half amplitude” auditory weak and strong stimuli
- deltaV: distance from “half amplitude” visual weak and strong stimuli

Use the following code to read a single person’s data.

```
# Needs to be installed from CRAN
# Needs a working perl installation, e.g. Strawberry perl
library(gdata)
set.seed(4711) # Eau de Cologne

rmie.read = function(fname='choice1.xlsx')
{
  d = read.xls(fname)
  d$Cond = factor(paste(d$stimA, d$stimV, sep=''),
    levels =c("00", "a0", "0v", "av", "A0", "0V", "AV"),
    labels =c("C", "a", "v", "av", "A", "V", "AV"))

  # Exclude training block
  d = d[d$Block > 0, ]

  # Omitted responses: response time = infinity
  d$resp[is.na(d$resp)] = 0
  d$RT[d$resp == 0] = Inf

  # SOA: Add SOA to RT in unimodal stimuli (see Eq. 1 in Miller, 1986)
  d$soaRT = d$RT
  d$tau = d$estim_SOA
  d$soaRT[d$Cond == "a"] =
    d$RT[d$Cond == "a"] + pmax(0, d$tau[d$Cond == "a"])
  d$soaRT[d$Cond == "A"] =
    d$RT[d$Cond == "A"] + pmax(0, d$tau[d$Cond == "A"])
  d$soaRT[d$Cond == "v"] =
    d$RT[d$Cond == "v"] + pmax(0, -d$tau[d$Cond == "v"])
  d$soaRT[d$Cond == "V"] =
    d$RT[d$Cond == "V"] + pmax(0, -d$tau[d$Cond == "V"])
  return(d)
}
```

Test of the race model inequality

This is the permutation test of the race model inequality (Gondan, 2010) for redundant signals with onset asynchrony (Miller, 1986).

```
tmax = function(di)
{
  tvalues = rowMeans(di) / apply(di, 1, sd) * sqrt(ncol(di))
  tvalues[is.na(tvalues)] = 0
  max(tvalues)
}

rmi_perm = function(d, quantiles=c(.05, .10, .15, .20, .25, .30),
                     cond=list(A='A', V='V', AV='AV', C='C'), nperm=10001)
{
  dc = d[d$Cond %in% cond, ]

  l = split(dc[, c('Cond', 'soaRT')], dc$Sub)
  for(i in 1:length(l))
    l[[i]] = split(l[[i]]$soaRT, l[[i]]$Cond)

  tmix      = lapply(l, unlist)
  q         = lapply(tmix, quantile, probs=quantiles, type=4)

  # Evaluate distribution functions at q
  FA        = mapply(function(ti, qi) ecdf(ti[[cond$A]])(qi), l, q)
  FV        = mapply(function(ti, qi) ecdf(ti[[cond$V]])(qi), l, q)
  FAV       = mapply(function(ti, qi) ecdf(ti[[cond$AV]])(qi), l, q)
  FC        = mapply(function(ti, qi) ecdf(ti[[cond$C]])(qi), l, q)

  # Determine di = FAV(q) - FA(q) - FV(q)
  di        = matrix(FAV + FC - FA - FV, nrow=length(quantiles),
                     ncol=length(l))

  # Observed test statistic
  stat      = tmax(di)

  # Permutation distribution of test statistic
  stati = numeric(nperm)
  for(i in 1:nperm)
    stati[i] = tmax(di %%% diag(sign(rnorm(length(l)))))

  list(tmax=stat, tcrit=quantile(stati, 0.95, type=8), P=mean(stat <= stati))
}
```

Go/Nogo-task

Respond to strong stimuli

Data from 5 participants performing a Go/Nogo task with strong stimuli as targets.

```
s1 = rmie.read('go-strong1.xlsx')
s2 = rmie.read('go-strong2.xlsx')
s3 = rmie.read('go-strong3.xlsx')
s4 = rmie.read('go-strong4.xlsx')
s5 = rmie.read('go-strong5.xlsx')
s = rbind(cbind(Sub=1, s1), cbind(Sub=2, s2), cbind(Sub=3, s3),
          cbind(Sub=4, s4), cbind(Sub=5, s5))

# Correct responses to "Go" trials
rmi_perm(s, cond=list(A='A', V='V', AV='AV', C='C'))

## $tmax
## [1] 5.439201
##
## $tcrit
##      95%
## 5.439201
##
## $P
## [1] 0.0589941

# False alarms to "Nogo" trials
rmi_perm(s, cond=list(A='a', V='v', AV='av', C='C'),
          quantiles=c(.02, .04, .06, .08, .10, .12))

## $tmax
## [1] 1.414214
##
## $tcrit
##      95%
## 3.826757
##
## $P
## [1] 0.6237376
```

Respond to weak stimuli

Data from 5 participants performing a Go/Nogo task with weak stimuli as targets.

```
w1 = rmie.read('go-weak1.xlsx')
w2 = rmie.read('go-weak2.xlsx')
w3 = rmie.read('go-weak3.xlsx')
w4 = rmie.read('go-weak4.xlsx')
w5 = rmie.read('go-weak5.xlsx')
```

```

w = rbind(cbind(Sub=1, w1), cbind(Sub=2, w2), cbind(Sub=3, w3),
          cbind(Sub=4, w4), cbind(Sub=5, w5))

# Correct responses to "Go" trials
rmi_perm(w, cond=list(A='a', V='v', AV='av', C='C'))

## $tmax
## [1] -1.537412
##
## $tcrit
##      95%
## 5.078334
##
## $P
## [1] 0.9686031

# False alarms to "Nogo" trials
rmi_perm(w, cond=list(A='A', V='V', AV='AV', C='C'),
          quantiles=c(.02, .04, .06, .08, .10, .12))

## $tmax
## [1] -1
##
## $tcrit
##      95%
## 3.148588
##
## $P
## [1] 1

```

Choice task

Data from 5 participants performing a choice task with weak and strong stimuli

```

c1 = rmie.read('choice1.xlsx')
c2 = rmie.read('choice2.xlsx')
c3 = rmie.read('choice3.xlsx')
c4 = rmie.read('choice4.xlsx')
c5 = rmie.read('choice5.xlsx')
c = rbind(cbind(Sub=1, c1), cbind(Sub=2, c2), cbind(Sub=3, c3),
          cbind(Sub=4, c4), cbind(Sub=5, c5))

# Analysis of fast and correct responses (w = weak, s = strong)
cc = c
cc$soaRT[!cc$ACC] = Inf # incorrect responses = infinitely slow

# Weak stimuli
rmi_perm(cc, cond=list(A='a', V='v', AV='av', C='C'))

```

```

## $tmax
## [1] -1.900511
##
## $tcrit
##      95%
## 3.090733
##
## $P
## [1] 0.9658034

# Strong stimuli
rmi_perm(cc, cond=list(A='A', V='V', AV='AV', C='C'))

## $tmax
## [1] 0.9460998
##
## $tcrit
##      95%
## 4.669738
##
## $P
## [1] 0.4991501

# Incorrect responses
ci = c
ci$soaRT[ci$ACC] = Inf # correct responses = infinitely slow
rmi_perm(ci, cond=list(A='a', V='v', AV='av', C='C'),
          quantiles=c(.02, .04, .06, .08, .10, .12))

## $tmax
## [1] 1.176697
##
## $tcrit
##      95%
## 3.64529
##
## $P
## [1] 0.5037496

rmi_perm(ci, cond=list(A='A', V='V', AV='AV', C='C'),
          quantiles=c(.02, .04, .06, .08, .10, .12))

## $tmax
## [1] -1.632993
##
## $tcrit
##      95%
## 3.43515
##
## $P
## [1] 1

```

References

Gondan, M. (2010). A permutation test for the race model inequality. *Behavior Research Methods*, 42, 23–28.

Miller, J. (1986). Timecourse of coactivation in bimodal divided attention. *Perception & Psychophysics*, 40, 331–343.